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CREDIT DEFAULT SWAPS: WHAT ARE THESE PRODUCTS AND WHAT INFLUENCES ITS PRICES?

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ABSTRACT

This thesis starts by describing credit default swaps (CDS), their benefits, costs, and how the market for these credit derivatives has been evolving in the past years. The main question that this thesis aims to answer is what are the factors that influence the prices of these financial products. The period under analysis goes from January 2006 to December 2016, and a sample of 72 European non-financial companies has been used. Through an econometric study using panel data regressions, the three theoretical determinants – leverage, risk-free rate and volatility - proposed by Merton's model are firstly tested. All variables are found to be statistically significant but the low explanatory power of this regression (14.88%) suggests there are other factors influencing CDS prices. By considering additional variables accounting for firm, market and liquidity factors, the explanatory power of all determinants more than doubled (34.33%). In addition, there is a multi-period analysis where all the determinants are analysed in different periods of the whole sample to check for changes in their significance. The main conclusion is that the theoretical determinants have rather limited power when explaining CDS prices and therefore other variables should be, though carefully, considered. In addition, not all variables have always had the same significance when explain CDS price changes. This thesis ends with a consideration of its limitations, and some suggestions to overcome these issues.

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Keywords: *Credit Default Swaps, CDS spreads, explanatory variables, structural models, Merton's model, regressions.*

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Introduction

Derivatives are financial instruments designed to reduce the uncertainty coming from a variety of sources such as exchange or interest rates, commodity or equity prices, and also credit. Given the wide range of derivatives there is and the variety of benefits and uses these bring, companies can minimize uncertainty across almost all their activities with the help of derivatives and hence generate future growth.

A vital part for the world's economic growth is financial activity. And a vital part for a successful financial activity are proper risk management practices. As such, risk management comprises the identification and development of procedures to minimize the impacts of the risks that affect the businesses of both banks and companies. Within the risks that are present among businesses is credit risk – the risk that a debtholder might not meet its contractual obligations when a credit event occurs, resulting in a loss for the borrower. To minimize this risk, credit derivatives, with the special focus on credit default swaps (CDS), have been created, as these provide an insurance against the risk of a credit event. Simply put, a CDS contract comprises two parties, where one buys the insurance by paying periodic instalments (CDS spreads) to the insurance provider who in case of a credit event pays the protection, and a third party, which is the party the contract is written on. But what influences the prices of those periodic instalments? It all started in 1974 when Robert Merton developed the first model to price credit risk, where the firm's asset value is related to credit risk and where three determinants appeared to answer the previous question – firm's leverage, risk-free rate, and assets' volatility[1]. Throughout the years, however, other models have been developed in order to better answer more properly to what moves those prices.

[1] Under Merton's model, the assets' volatility is not historical - it is the true volatility that characterizes the assets distribution going forward. Nonetheless, while in empirical work historical volatility may be used as its proxy (as it will be in this case), there are other alternatives.

In addition to the models developed the years, previous empirical studies have tried to understand the different measures of credit risk. Two of the most important studies in the field are Collin-Dufresne, Goldstein & Martin (2001) (CGM) and Ericsson, Jacobs and Oviedo (2004) (EJO), and will serve as references for many of the upcoming sections of this thesis. CGM tried to investigate the issue by using bonds credit spreads, while EJO used CDS spreads for their analysis. According to other authors, the use of CDS spreads is however is preferable since these are quotes from actual dealers, while bond prices do not necessarily reflect the prices at which the trades happen (Hull, Predescu, & White, 2004) and, besides mirroring credit risk, CDS spreads also reflect bonds' illiquidity (Longstaff, Mithal, & Neis, 2005). As the market for CDS appears to be more liquid than the bond market, CDS spreads seem to be better indicators of credit risk. To complement, not only the CDS market responds faster to changes in firms' credit risk than the bond market, but also the use of bond spreads implies the choice of the most appropriate risk-free benchmark rate, which is a rather difficult task. Having pointed out all the reasons above, this thesis makes use of CDS spreads in the study of their determinants.

This master thesis aims to be a valuable tool for anyone who is interested in knowing more about CDS, by answering to questions such what are these products, what are their benefits and concerns, how the market for these credit derivatives has been developing, and ultimately what influences the prices of credit default swaps. In the econometric section of this study, there is a first part which intends to find how well the theoretical determinants derived by Merton are able to explain the prices of CDS, followed by other regressions with additional possible determinants that will be further explained. As a final analysis, this study examines different periods of the entire sample, in order to test the effect of different economic events in the determination of CDS prices. All the results and findings are later on presented, followed by the conclusion and limitations sections concerning this master thesis.

1 - What Are Credit Default Swaps?

When any investment is made, there are different types of risk associated that can be categorized into different risk sources. For instance, when an investor buys bonds of Unilever in Euros, there are several risks associated: interest rate risk, i.e. the risk that the European Central Bank might follow a contractionary monetary policy; currency risk, i.e. the risks that the Euro might devalue relative to the US dollar; credit risk, i.e. the risk that Unilever might not be able to achieve its financial liabilities on time and consequently enter in default. Relatively to the last risk previously mentioned, there is a wide range of credit derivatives, whose main goal is to mitigate credit risk by isolating it from the contract and transferring it to a third party who is willing to assume this risk for a pre-defined fee. Essentially, the main idea behind credit derivatives the relocation of credit risk from one party to another.

Although there is a vast range of instruments used to transfer credit risk, their classification is rather simple, and it is done according to each instrument specific characteristics – credit risk may be transferred through either single (single name) or multiple borrowers (multi name), and the underlying asset in each transaction may be sold (funded) or not (unfunded).

Credit default swaps (CDS) are a type of unfunded risk instruments, are widely used by investors all over the world, and are the most popular instruments for trading credit risk. A credit default swap is no more than a bilateral over-the-counter agreement between two entities used to transfer the credit risk of a given underlying from one entity to another.

A "plain vanilla" CDS is a contract between two parties in which the protection buyer of the CDS pays fixed periodic premiums to the protection seller until the maturity of the CDS, or until a specific credit event happens. In the case of a credit event, the deal is settled since the protection buyer receives either a physical or cash payment from the protection seller, according to the specifications of the agreement. If there is no credit event during the time of the agreement, no payment if made to the buyer. The common terminology used to describe the flows of payments are the fixed leg (fixed premiums paid by the buyer) and the contingent leg (payment by the seller contingent on the credit event).

Instead of viewing a CDS contract as a transaction of protection, it can also be seen as a transaction of credit risk. When looking at it this way, the protection buyer is the seller of the credit risk, as he could simply sell the underlying asset which would immediately reduce his exposure to credit risk and, similarly, the protection seller is the credit risk buyer, as he could gain exposure to credit risk by buying the underlying asset. In fact, the CDS is, many times, a cheaper alternative to gain or reduce the exposure to the underlying's credit risk relatively to buying or selling the asset, respectively. This is one of the reasons that make CDS so popular among investors – a cheaper alternative to increase or decrease exposure to credit risk.

Regarding the payment structure of CDS, the fixed leg paid by the protection buyer is derived as a percentage of the notional amount of the underlying asset, and the common periodicity for the payments is quarterly. The total amount of premiums paid per year by the protection buyer corresponds to the CDS spread and it is quoted in basis points. In addition to the payment structure, it is important to understand what are the credit events (the scenarios in which the protection payment is made) that trigger the payment from the protection seller to the buyer. The three most common credit events are: Bankruptcy – when the underlying firm becomes insolvent and cannot repay its debt; Failure to Pay – when the underlying, after a grace period, fails to pay either the principal or interest on its liabilities pay (values must be subjected to a materiality threshold); Restructuring – when there is an alteration to the terms of debt obligations that is unfavorable to creditors such as lower coupons or lengthier maturity.[2]

After the credit event is triggered and confirmed by a central decision-making entity[3], the settlement of the CDS is made via cash or physically. When CDS are cash settled, the protection

[2]More about this in Bomfim, 2005

[3]The Determination Committee was created in 2009 to deal with different issues regarding the settlement conditions and procedures (Chaplin, 2010)

buyer receives the difference between the face and market value of the reference obligation from the protection seller, where the market price is usually defined by an auction of dealers who define the final market price. In this case, the reference obligation refers to the underlying's debt predefined in the CDS contract, and normally corresponds to senior unsecured bonds. On the other hand, when CDS are settled physically, the protection buyer has the right to sell a variety of deliverable obligations to the protection seller, who in turn must pay their full face value. These deliverable obligations correspond to any obligation that has the same rank in the underlying's capital structure as the reference obligation (Bomfim, 2005). Cash settlements are the method most commonly used to settle CDS contracts (Chaplin, 2010).

Besides plain vanilla CDS, other types of CDS such as digital CDS, loan-only credit default swaps (LCDS), and CDS indexes also exist in the market. Digital CDS are contracts where the payment made in the case of a credit event is a fixed amount and therefore does not depend on the market value of the obligations at default. LCDS have the same structure of simple CDS, except that the underlying entity is restricted to syndicated secured loans, rather than any bond or loan[4]. CDS indexes are portfolios of single-name CDS that allow investors to transfer credit risk of a wide range of credits in a much more efficient way than by dealing with single-name contracts. In fact, CDS indexes are the most liquid financial instruments in the credit market nowadays.

1.1 - The Good

Credit default swaps have gained a major popularity in financial markets in the past years thanks to the various benefits that will now be discussed.

Given their structure, credit default swaps allow for risk diversification of the market participants. For example, these products can help financial institutions to hedge part of their

[4]In Europe, LCDS are used as a hedging product, whereas in the US their use and trade is seen as an investment strategy. European banks, which are the main originators of syndicated secured loans, use these contracts as hedging products to manage their loan books and decrease regulatory capital (Bartlam & Artmann, 2007)

credit exposure with the acquisition of protection in case of credit events. In practice, bank A may be asked by company X to grant it a loan in addition to those that the company already has under bank A's balance sheet. If the bank does not want to incur in the loan because it sees it as a risky operation that would only increase the risk exposure to company X, the bank can incur in a CDS contract on company X with a third party to offload part of the credit exposure instead of rejecting the operation right away. This way the bank is able to not only finance the company's operation and increase its profits, but also to manage its exposure and diversify the risk. CDS contracts are therefore tools that minimize credit risk from operations. From another perspective, bank A may also be interested in gaining exposure to different industries without the need to supply credit. Instead, the bank can sell protection for these companies in the CDS market and consequently gain exposure to the chosen industries. All in all, credit default swaps are useful tools for risk management purposes, as banks can use them according to their preferences. The same reasoning can be applied to individual or institutional investors. If, for instance, investor B has a long position on company's Y bonds, he may enter in a CDS contract to prevent his losses in the event that company Y enters in default.

Besides the benefits of diversification, credit default swaps are highly valuable tools when assessing one company's credit risk. Although credit ratings do exist for the same purpose, they are generally a reactive instead of a proactive response to alarming signals, many times are inconsistent and do not provide much insightful information, as history tells (in the beginning period of the 07/08 financial crisis, many entities had their ratings overestimated despite many suspicious indicators). In addition, there are evidences that the market for CDS absorbs new information about credit risk faster than rating announcements (Hull, Predescu, & White, 2004) and (Norden & Weber, 2009). As such, the CDS market is generally seen as a more insightful source of information than the bond market when assessing how fast credit risk information is incorporated. This characteristic therefore increases the transparency in the market and allows participants to make better informed judgements on companies' credit risk.

In addition to these benefits, the creation of the Determination Committee to help with the issues regarding the proper definition of credit events, how the settlement procedures should be done and what type of obligations are valid when settling a contract has helped the CDS market to gain reliability and acceptance amongst market participants.

1.2 - The Bad

Despite the numerous benefits that CDS have for market participants, there are also some risks regarding the use of these financial products that need to be considered. The financial crisis of 07/08 has highlighted some of the drawbacks of credit default swaps, and in fact, many have pointed out these as one of the main reasons for the burst of the world financial markets and economy.

Within the CDS market, two risks became evident during the financial crisis: counterparty risk, concentration risk, and the relationship between the two. Counterparty risk – the risk that at least one of the counterparties does not meet the contractual obligations of the agreement – is a transversal risk to all over-the-counter derivative markets (markets in which the transactions are private contracts negotiated between two entities without recurring to intermediaries such exchanges) that as been intensified by concentration risk – risk there is a high concentration of sellers and dealers in a market. According to different surveys, the top ten counterparts of each large bank in Europe accounted for about two third of the banks' credit exposure in 2009 (European Central Bank, 2009), while in the US more than 90% of the credit derivative exposure of one hundred companies during the first quarter of the same year was concentrated among Bank of America, Citigroup, Goldman Sachs, JP Morgan and Morgan Stanley (Fitch Ratings, 2009).

The problems of having such a degree of counterparty and concentration risks have three main strands. Firstly, if one dealer enters in default, specially if it is large, the systemic risk increases, since the probabilities that others follow the same path in a chain effect increases. In addition, if there is a credit event one an entity that has been largely underwritten, large payments are activated, which also increases the correlation of default of the highly related dealers in the market. Last but not least, since the OTC markets are rather opaque when compared with exchanges, a default of either a dealer or a reference entity creates generates a high level of uncertainty among all participants which can lead to a steep decrease in the market liquidity.

In addition to the aforementioned risks, moral hazard, asymmetrical information as well as insider trading emerge as possible drawbacks within the CDS world. When considering the banking sector, since it becomes very costly to monitor loans to borrowers and because on top of that capital charges are high when holding risky loans, banks tend to find ways to avoid at maximum the associated costs. Within these ways are CDS contracts, which although being tools to reduce credit exposition, these are also a way that banks have to detach themselves from the borrowers with them to notice, which causes problems of asymmetrical information. In addition, this situation can cause the monitoring process of loans much sloppier and thus increase banks' control over the terms of the lending relationships, as there are no incentives to control borrowers properly given the protection from transferring credit risk. This situation can lead to moral hazard.

These information asymmetries can also cause the issue of insider trading, as banks possess inside and private information on the reference companies that can be used in their favour in the CDS market. As an example, a bank could try to exploit the private information it has on the likelihood of default of one of its clients by protection on the same client from a poorer informed counterparty. Given that the main bank dealers in the CDS market have strong relationships with some of their client companies, insider trading constitutes a serious problem.

Another major concern around the market CDS has been speculation and price manipulation. There are have been several critics that, during the financial crisis of 07/08, some market speculators have bought large amounts CDS contracts which consequently drove down the bond and stock prices of the underlying entities. By signalling problems regarding companies' solvency, speculators were able to take advantage of the uncertainty surrounding financial markets.

1.3 - The Market[5]

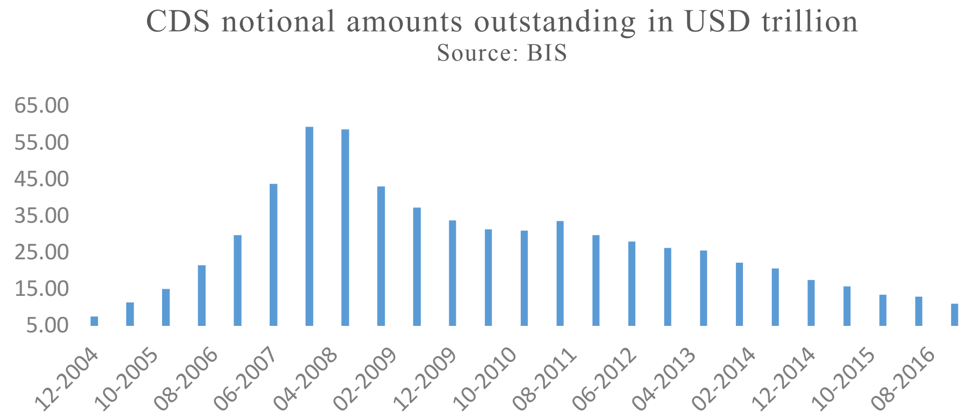
In 1997 JP Morgan created the first CDS contract ever. This event marked the beginning of the market for credit derivatives and ever since then the financial markets' landscape has never been the same. Since the beginning of the new millennium and until the burst of the financial in 2007, CDS contracts experienced remarkable growth rates. Nevertheless, the results published by the Bank for International Settlements (BIS) show that in in the first half of 2008, and for the first time since 2004 (date of the first results publication), the CDS volumes declined relatively to the numbers of the end of 2007. This variation was mainly driven by the credit market crunch caused by the financial crisis that lead to a portfolio compression by banks (a reduction of the portfolios notional amount and contracts outstanding in which the risk profile and cash flows remain the same) and to a decrease in the number of the market participants. Despite the decline in the outstanding volumes of credit default swaps, their gross market value actually increased by 58% during the same period.

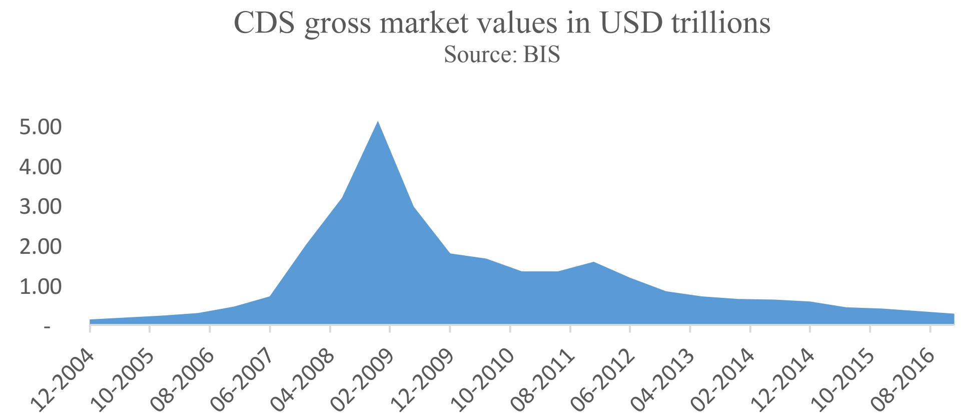
Given these seemingly contradictory variations, it is necessary to distinguish the difference between the concepts of notional outstanding and gross market value. While the notional outstanding is a reference point for the computation of contractual payments which is established at the beginning of contracts when their market value is zero, the market value varies along time since it is a reflection of the market expectations about the contract. When

[5] The graphs that show the market evolution can be seen in the end of this section's text.

contracts are established, if market values of CDS rise (drop) it is because default is more (less) likely to happen or because recovery rates are expected to be (lower) higher in the case of a credit event. All in all, gross market values are better indicators of the value of CDS contracts as they reflect better the underlying risks. As such, it makes sense the above values for the increase in CDS contracts gross market value, as the default risk highly increased with the start of the financial crisis in 2007.

During the following semesters, the notional amounts of CDS contracts experienced a sharp decline, and naturally the gross market values adjusted and started to decrease as well – by the end of 2009 the gross market value of CDS contracts had decreased 35% relatively to the beginning of the year. During the first half 2011, however, the notional amounts of CDS contracts actually increased 8% despite no significant changes were registered at their gross market values. By the end of the year though, the notional amounts had decreased once again, while the gross market values for CDS contracts increased which could have been caused by the strengthening of the USD in relation to other currencies due to the Eurozone crisis (CDS data is expressed in US dollars). For the upcoming years, a downward trend characterized the evolution of both the notional amounts and gross market values for CDS contracts (see graphs below), to a situation where as of December 2016, the notional amounts outstanding amount to $9.9 trillion, and the gross market values of CDS contracts amount to $292 billion. These values are specially striking when compared to their maximums – $58.2 trillion and $5.1 trillion respectively - which shows that the CDS market has been losing popularity, in result of not only the financial crisis, but also as consequence of the multiple cases of misuse with these credit derivatives that have resulted in major losses for many market participants.





2 - Credit Risk Models

There are two main approaches when modelling credit risk: structural models and reduced form models. This section will first comprise a broad analysis of structural models with special attention paid to Merton's model, followed by brief overview of reduced-form models, and finally a wrap up about the two approaches.

2.1 - Structural Models

In structural models, the dynamics of a firm's asset value are explicitly modelled and there is a clear connection between credit risk and a firm's fundamental variables. Under this approach, the firm is assumed to default if the total assets' value falls under a certain default threshold, and the main parameters affecting one's default probability are financial leverage, assets volatility and the risk-free interest rate.

Merton (1974) with his seminal model – a framework where: (1) the firm's assets value is related to its credit risk; (2) the Black and Scholes (1973) option pricing model is used to price defaultable bonds and the equity of the firm – has majorly contributed for this field, where many extensions have been developed throughout the years to overcome the shortcomings of the early models. Nonetheless, Merton's work still remains has a reference for today's credit risk management models such as CreditMetrics or Moody's KMV model.

There are four main types of structural models (Jakovlev, 2007): firm value models, first-passage models, liquidation process models and state dependent models. The rationale behind the existence of distinct types of models suggests a need to overcome the main drawbacks that each type of model presents.

Firm value models (e.g., Merton) consider that a firm's default can only occur at the maturity of its debt and therefore disregard the firm value before maturity. To overcome this situation, practitioners have developed first-passage models, that consider default scenarios when the firm's assets value drops for the first time below a certain "default barrier", which can happen anytime before or at maturity. This barrier (Beem, 2010) can be either defined as exogenous – outside the model - or endogenous – within the model. Given that these models allow for defaults to happen at any time until maturity, the probability of positive payoffs for the shareholders is, in this case, lower than the one implied by firm value models. Hence, both the probability of default and credit spreads implied by first-passage models are higher than, for instance, the ones implied by Merton's model, as it makes sense that investors should pay more to protect themselves against any eventual decrease in the firm's value below the default barrier. One remarkable example of this type of models has been developed by Black and Cox (1976).

Regarding liquidation process models and state dependent models, both have emerged as extensions with the purpose of incorporating different real-world occurrences into the existent structural models. In liquidation process models, if a firm's assets fall under the default threshold, it does not necessarily mean the firm's immediate liquidation contrarily to what other models assume. Instead, it means that the default will trigger an often long process which might, or not, lead in fact to the firm's liquidation. In the case of state dependent models, these extend structural models by incorporating some parameters that can be contingent upon the state, such as business cycles or the firm's external rating, and others such as bankruptcy costs, cash flows and financing costs (Elizalde, 2006). With these two types of models, and given the consideration of different phenomena when compared to standard structural models, the problems regarding the predictability of bankruptcies can be reduced. By including other parameters that influence the firm's ability to generate cash flows or its funding costs - main drivers of default probabilities -, some of the drawbacks of standards models can be counterbalanced (Gruiescu, Ungureanu, & Ioanas, 2012).

In order to better understand the dynamics of structural models, and as a basis for the upcoming sections (the econometrical part of this paper will be evaluated from the perspective of structural form models), the model developed by Merton (1974) along with its main implications and drawbacks will be discussed more in depth.

2.2 - Merton's Model

The framework developed by Robert C. Merton (1974) has set the ground rules for the vast range of structural models that currently exist in credit risk. Simply put, the underlying idea behind this framework is that credit events can be explicitly related to the firm's assets value by making use of the Black & Scholes options pricing model to price corporate liabilities, where the final output is the firm's credit spread. This is a rather straightforward process, but only if some assumptions and conditions are fulfilled a priori. In order to understand the mechanics of Merton's model, the fundamental assumptions as well as the default conditions that need to be met will now be specified.

Within the model there are no transaction nor bankruptcy costs, no taxes, and hence the Modigliani-Miller theorem holds. Besides, assets' trading is continuous, there are no restrictions regarding the short-selling of assets, and the risk-free interest rate r is known and constant at any point in time. Regarding the assets' value V_t, firms are assumed to have simple capital structures comprised by equity E_t, and debt as a single zero-coupon bond with maturity T, face value F, and current market value B_t. Thus, the firm's market value can be described as $V_t = E_t + B_t$. In addition, and to allow for the computation of the default probabilities over time, the dynamics of the assets' value V_t under Merton's model take the form of a geometric Brownian motion

$$dV_t = \mu dt + \sigma dW_t \quad (1)$$

where W_t is a standard Brownian motion that follows a normal distribution $W_t \sim N(0, t)$ with independent increments, and μ and σ correspond respectively to the mean and standard deviation of the assets' returns.

As Merton Model assumes that default can only happen at maturity T, and given that default happens when the value of assets at maturity falls below the face value of debt, there are two possible scenarios at $t = T$ - survival or default. If the firm survives, $V_t > F$ which means the firm is able to pay back its debt, and that the firm's shareholders will have a payoff equal to $V_t - F$. In the event of default, $V_t < F$ and consequently the firm enters in default by not being able to pay back its debt face value to bondholders. Under the latter scenario, bondholders get the amount V_t while taking control of the firm, making the payoff for shareholders equal to zero. To sum up, the aforementioned payoffs at maturity can be written as:

$$E_t = \max(V_t - F; 0) \quad (2)$$

$$B_t = \min(F; V_t) = F - max(F - V_t; 0) \quad (3)$$

	Survival ($V_t > F$)	Default ($V_t < F$)
E_t	$V_t - F$	0
B_t	F	V_t

The central idea around Merton's model lies precisely in the way these payoffs are interpreted. Under the conditions imposed by the model, the equity's payoff has the same behavior of a call option on the firm's assets with maturity T and strike price equal to F. Thus, using the Black & Scholes call option formula, it is possible to compute how much the firm's equity is worth[6]:

$$C_0 = V_0 N(d_1) - Fe^{-iT} N(d_2) \tag{4}$$

The firm's debt payoff, which is essentially a bond with default risk associated, has the same behavior of a portfolio comprised by two securities: a risk-free bond F with maturity T, and a short position of a put option P_0 on the firm's assets with maturity T and strike price equal to F. In fact, this portfolio's present value (value of the defaultable bond) is nothing more than the present value of the risk-free bond discounted at the risk-free interest rate plus the present value of the short put position, which can be computed through the Black & Scholes put options pricing formula, i.e.,

$$B_0 = Fe^{-iT} - P_0 \tag{5}$$

by using the Black & Scholes formula,

$$P_0 = Fe^{-iT} N(-d_2) - V_0 N(-d_1) \tag{6}$$

where,

$$d_1 = \frac{\ln(V_0/F) + (i + \sigma^2/2)T}{\sigma\sqrt{T}} = \frac{\ln \frac{V_0}{Fe^{-iT}} + \sigma^2 T/2}{\sigma\sqrt{T}} \tag{7}$$

$$d_2 = \frac{\ln(V_0/F) + (i - \sigma^2/2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T} \tag{8}$$

[6] This formula's parameters will be explained in depth upon the application of the put option formula

with $N(.)$ representing the standard normal cumulative density function and V_0 the initial assets' value. Note that in d_1 there is a ratio between the present value of the risk-free debt and V_0, which in fact corresponds to the inverse of the firm's leverage ratio ($L \equiv Fe^{-iT}/V_0$).

As the debt of the firm can be seen as a risky bond and priced as such, it is also possible to calculate its yield to maturity:

$$B_0 = Fe^{-ytmT} \Leftrightarrow ytm = -\frac{1}{T} ln \frac{B_0}{F} \tag{9}$$

And as the yield to maturity of this risky bond corresponds to the risk-free interest rate plus the default risk, the default spread s is simply the difference between the yield to maturity and the riskless rate.

$$ytm = i + s \Leftrightarrow \; s = ytm - i \tag{10}$$

To calculate the default spread, the final step is to substitute the ytm term by (9), B_0 for (5) and P_0 for (6). Instead of these arithmetical gymnastics, the credit spread - Merton's model main output - can be directly computed through:

$$\begin{gathered} s = ytm - i \\ = -\frac{1}{T} ln \frac{Fe^{-iT} - P_0}{F} - \frac{1}{T}(-1)\, ln\, e^{-iT} = -\frac{1}{T} ln\left(1 - \frac{P_0}{Fe^{-iT}}\right) \\ \boldsymbol{s = -\frac{1}{T} ln\left(N(d_2) + \frac{V_0}{Fe^{-iT}} N(-d_1)\right)} \end{gathered} \tag{11}$$

All in all, this is the essence of Merton's model, the first structural model designed for modeling credit risk. Within the model, and as the above formulas imply, there are only three theoretical determinants that become necessary to price credit risk: leverage, risk-free rate, and historical volatility. Although the simplicity that characterizes this model allows for a simple and rather quick application of credit risk to firms, there are some limitations around the process that have led to the development of new and more complex models throughout the years.

2.3 - Merton's limitations and extensions

In Merton's model firm's debt is modeled as a simple zero coupon bond structure, and this naturally does not correspond to what happens in reality. As so, other models (Geske, 1977) that consider more complicated debt structures such as debt coupons, debt subordination, payout restrictions, sinking funds or safety covenants have been developed to deal with this situation.

In addition, Merton considers that default can only happen at the maturity of the debt, while in practice companies can default at any time due to any financial obligation. To deal with this problem, the already mentioned FPM (first-passage models) have been developed.

Another naive inference in Merton's model is that interest-rates have constant and flat behaviors. In fact, several authors in the literature have considered and incorporated stochastic interest rates along with taxes to increase the model's quality. This has been the case of, among others, Jones et al. (1984), Ronn and Verma (1986), Nielsen et al. (1993) or Longstaff and Schwartz (1995). Besides these limitations, Merton also assumes that the firm's value is tradable. Here, an unrealistic situation arises in the sense that the firm's value as well as its underlying parameters cannot be directly observed. Nonetheless, assigning the right dynamics to the value of the firm is not an exclusive challenge of Merton's model, but of all structural models, as the procedures differ from one model to another. Even if the value is extracted directly from balance sheet data, the methods to reach the firm value are often highly sensitive to the assumptions and methods used.

2.4 - Reduced-Form Models

Contrarily to structural models where default is endogenously derived from specific model conditions, reduced-form models treat default in an exogenous manner where the parameters are extracted from past bond prices data. Although this means that no economic explanation is provided for the occurrence of default, the fact that default is specified through an exogenous stochastic process greatly simplifies the whole process in reduced-form models. All in all, the main idea behind this type of models is that credit events occur unexpectedly. There are two main modelling processes that give rise to reduced-form models, one related to the evolution of risk-free interest rates and another for the likelihood of default. Nonetheless, there is another exogenous process that in principle could be specified, which is related to the determination of recovery rates, although in practice constant recovery rates are commonly used in these models. Usually, under this approach, the default likelihood is modelled through an intensity process (that can take one of various forms – constant intensity, time-varying intensity, stochastic intensity) in which the intensity represents the likelihood of default over any given time horizon, and the higher the intensity, the higher the likelihood of default. Within reduced form-models there are various of relevance, such as the Litterman-Iben Model (1991), and the Jarrow and Turnbull model (1995).

Nonetheless, as the focus of this paper consists of a study based on the determinants according to credit risk structural models and more specifically Merton's model, I will not take a deep approach with respect to reduced-form models.

2.5 - Structural Models and Reduced-Form Models: Wrap up

So far, both structural models as well as reduced-form models have been discussed. Although the mechanics as well as the assumptions of each model obviously differ from one model to another, if there is one major difference between the two types that should be mentioned, it would have to be about the amount of information that is available under each scenario. Structural models assume that the information available is equivalent to the one held by the firm's manager, in the sense there is total knowledge about all the firm's assets and liabilities, which implies that the default time is predictable. Contrarily to this view, reduced-form models assume that the information that exists is the one that is exclusively perceived by the market. This less complete information set therefore suggests that there is no knowledge on the time of default, and hence default is characterized by uncertainty. Indeed, reduced form-models need less knowledge on the firm's capital structure than structural models to draw any conclusions, but that should not be enough to prefer one type over another.

As pointed out in the literature, the question should not be which model is the best in terms of performance, but whether or not the models should base the assumptions on the information set present in the market or not (Jarrow & Protter, 2004). Nonetheless, many authors agree that the asset value process is not observable by the market (Duan, 1994) (Ericsson & Reneby, 2002) (Ericsson & Reneby, 2003), and therefore there is a general consensus around the adoption of reduced form models in favour of structural models to price and hedge credit risk. Of course this choice depends on the purpose for which the model is to be used. If one desires it for pricing a firm's risky debt or its related credit derivatives, reduced-form models should be preferred. However, if one represents the management within a firm, and if there is enough information available, then structural models may be preferred to assess the firm's default risk for capital considerations for instance.

In terms of performance, there are several case studies that test the validity and strength of both approaches. For instance, the study from Arora et al. (2006) tests the performance of two structural models (Merton's model and Vasicek-Kealhofer – an extension of Merton that considers more classes of liabilities, cash payouts, and where default can happen at any time – for more info please refer to KMV EDF model) against one reduced-form model (Hull-White model) and conclude that Merton's model significantly underestimates spreads while VK and HW models overestimate the same spreads. Overall, VK, the structural model, performs better than the reduced-form model HW and the simple Merton model (Arora, Bohn, & Zhu, 2006). This, however, does not necessarily mean that structural models should always be used, as it has been already discussed before.

Still regarding the performance of the models, the results concerning Merton from the previous case study are consistent the existing literature on the subject. Jones et a. (1984), and Huang & Zhou (2008) have also reached the same conclusion in their studies that the model prices are much smaller that the equivalent market prices of CDS spreads, specially for shorter maturities. This disparity could be related with the already discussed limitations around Merton's model. However, the underlying reason for the poor performance in computing credit spreads is yet to be clarified. As in Merton's model the firm's asset value is modelled as a Geometric Brownian Motion, and that default can only happen at maturity, default predictability increases as the maturity of the debt comes closer. As so, a scenario of default is not a surprise anymore, and therefore short term credit spreads are very close to zero. Jeroen van Beem (2010) illustrates this problem with a series of graphs that show how both the probability of default and the CDS spreads are zero for short maturities.

Nevertheless, Merton's model is not the only one that suffers from the underestimation of market credit spreads. Overall, market CDS spreads are much higher than the ones computed from credit risk models, since there seems to be an overcompensation for the existing levels of risk – commonly known as the credit spread puzzle. In conclusion, there are more factors affecting market spreads than just credit risk.

The next sections of this thesis, namely the econometric study, will focus on the analysis of some of the factors that should be considered when computing CDS spreads. Whether these factors make economic or rational sense, the reasoning for their inclusion as well the impact on the market CDS spreads will be clarified, in an attempt to find out more about what moves the prices of these financial products.

3 - Data and Methodology

The following section is the basis for the econometric study of this paper. Nevertheless, and before presenting the methods used in the regressions and the subsequent results, it is necessary to explain which variables have been used in this report. The CDS determinants that have been chosen for the regressions can be divided in three main groups: theoretical determinants, firm based determinants, and market based determinants. In addition, a variable to account for the liquidity of CDS contracts has also been added, along with a lagged CDS variable. Besides the explanations for each variable, and how each one affects CDS spreads according to the existent literature, the methods for data collection will also be clarified.

3.1 - Data

Since the purpose of this study is to investigate the determinants of CDS in European companies, and to define a representative sample of the European paradigm, the data that has been collected refers to the STOXX Europe 600 Index constituents, which represents large, mid and small capitalization companies across 17 European countries. However, several steps were required in order to reach the final sample of companies. From the 600 components of the index, American companies that are represented in this index have removed, as well and the ones operating in financials sectors, in order to have a comparable basis of firms in terms of balance sheet information. Moreover, the sample period for the analysis consists of monthly observations during 01/01/2006 to 31/12/2016. All data was collected from Bloomberg.

3.2 - Dependent Variable

The CDS sample used in this paper consists of monthly quotes on 5-year CDS contracts (cds) of the aforementioned firms. This maturity was chosen since these are the most liquid contracts available in the market (Carol & Kaeck, 2007) (Ericsson, Jacobs, & Oviedo, 2004). However, not all companies had 5-year CDS contracts ticker available, and of those who had, not all information was available. As so, and in order to only work with companies where full information was available and that did not default over the entire sample period, the final sample has 72 companies represented (see Appendix 1).

3.3 - Explanatory Variables - Theoretical Determinants

In order to be line with the studies of EJO and CGM, the theoretical determinants used in this paper will be the same as the ones assumed in Merton's model. As so, leverage, the risk-free rate and historical volatility will now be discussed.

3.3.1 - Leverage

Under Merton's model, firm's leverage is a crucial determinant of credit spreads. According to the model, if the assets value is less than the debt's face value at maturity, the firm enters in default. As such, the higher the leverage the higher the default risk. Intuitively, all things else equal, a firm that incurs in more leverage should see the price of its insurance against default increase (higher CDS spread), which suggests a positive relationship between the two variables. In fact, this positive relationship is confirmed in several studies, such as EJO and CGM.

To collect data from companies, monthly leverage ratios have been calculated according to CGM's formula, using the book value of total liabilities and market value of equity from Bloomberg. Leverage (lev) is therefore defined as:

$$lev = \frac{Book\ Value\ of\ Total\ Liabilities}{Book\ Value\ of\ Total\ Liabilities + Market\ Value\ of\ Equity}$$

3.3.2 - Risk-free rate

The risk-free rate is also considered under Merton a key determinant for firms' credit spread, and despite the erroneous assumption of a constant rate throughout the time period, some conclusions can still be drawn of how it affects the spread. An increase in the risk-free rate, ceteris paribus, should decrease the credit spread. The reasoning is that higher risk-free rates increase the risk-neutral drift of the firm's value, and consequently the probability of default decreases (Blanco, Brennan, & March, 2005). Evidences from this relationship can be found in the studies of Longstaff and Schwartz (1995), Duffee (1998) and CGM (2001).

As CGM and EJO use a 10-year government rate as proxy for the risk-free rate, a 10-year rate was also used in this case to be in line with the literature. More specifically, the yield used was the 10-year German government bond ($r^{10-year}$), as these bonds have higher liquidity and lower credit risk when compared to other European countries (Koller, Goedhart, & Wessels, 2005). In addition, the 2-year German government bond was also used (r^{2-year}) in the regressions, following the studies of CGM and EJO. Since the two rates have strong correlation, the 2-year yield was used in the main regression (whereas the 10-year rate was only used in the regression with the theoretical determinants), along with the square of the 2-year rate $(r^{2-year})^2$ to account for convexity issues and capture potential nonlinear effects (Collin-Dufresne, Goldstein, & Martin, 2001).

3.3.3 - Historical Volatility

Historical volatility is the final determinant that affects firms' credit spread according to Merton. Since firms' volatility is not possible to observe directly, there are several proxies for it, being the historical volatility – based on past stock performance - the most common of those. In theory, all else constant, a higher volatility increases the probability of default. The reason for this is that if the volatility of the underlying is higher, there is a higher probability of put option on the firm to be exercised, since the number of scenarios where the firm enters in default increases, leading to an increase to the cost of the insurance – higher CDS spread. This relationship is again confirmed by different studies, such as CGM and EJO.

In order to retrieve the data for firms' historical volatility, this paper does not use the same approach as many others, which obtain time-series data of historical volatility from running windows of the previous 250 days' equity prices. Instead, the historical volatility ($histvol$) used in this paper was retrieved from Bloomberg, where it is possible to get directly the firms' 1-year (260 trading days) historical volatility for each month, for every firm.

3.4 - Explanatory Variables – Firm Based Variables

3.4.1 - Equity Return

The relationship between equity return and CDS spreads is rather straightforward. Higher stock returns imply that the firm is worth more, and the better the company is, the less likely it is default to happen. As such, a negative relationship between equity returns and CDS spreads is expected. With regards to its relevance, and although some equity market information is already incorporated into firms' leverage ratio, including this variable in the analysis allows for a clearer view on the influence of equity returns in CDS spreads. Besides, the correlation of equity returns with leverage is not too high, which indicates that the two contribute with different levels of information, as in accordance with CGM.

Equity returns ($eqret$) have been computed by taking series of monthly log returns of each firm. Using log-returns also allow for a better analysis since these are more normally distributed and symmetrical. (Black & Cox, 1976) (Black & Scholes, The pricing of options and corporate liabilities, 1973) (Black & Scholes, The pricing of options and corporate liabilities, 1973; Merton, 1974; Longstaff & Schwartz, 1995; Byström, 2006; Jones, Mason, & Rosenfeld, 1984; Baltagi, 2001; Coro, Dufour, & Varotto, 2013; Ronn & Verma, 1986)

3.4.2 - Implied Volatility

This variable, which is based on traders' expectations and can therefore be considered a good proxy for future volatility, comes as another measure of volatility. As implied option volatility tends to overshadow historical volatility (Cao, Yu, & Zhong, 2010), including this in the regressions may be advantageous. Besides, since the correlation between implied and historical volatility is not very high, it indicates that the two represent different measures. It is expected a positive relationship between implied volatility and CDS spreads.

This variable ($impvol$) has also been collected from Bloomberg, through continuous time-series of firms' implied put-option volatility.

3.5 - Explanatory Variables – Market Based Variables

3.5.1 - Yield Slope

The slope of the yield curve is a measure of expectations about the future economic conditions in the market. Intuitively, the higher the slope the higher the future rates (Carol & Kaeck, 2007), since there is an anticipation of future economic growth, and therefore the relationship between this variable and CDS spreads should be negative. Nonetheless, this relationship is not entirely consensual in the literature, with some authors inferring a positive relationship backed the adjusted present value theory (Galil, Shapir, Amiram, & Ben-Zion, 2014).

In line with both CGM and EJO, the yield slope ($slope$) is assumed to be the difference between the 10-year and the 2-year German government yield.

3.5.2 - Market Return

In order to capture the overall state of the European economy, monthly log-returns of the STOXX Europe 600 Index have also been used ($mktret$). Not only this variable helps to assess the importance of the business climate on CDS spreads, but it also serves as a proxy for systematic risk. As it has been previously mentioned, the motivation for using log-returns is that these are more normally distributed and symmetrical. It is expected this variable to have a negative relationship with CDS spreads, as higher market returns should indicate expectations of better future economic conditions.

3.5.3 - Market Volatility

As another measure to capture the business climate, market volatility ($mktvol$) has been considered in this study. Higher market volatility means there is more uncertainty about the future economic prospects of the market, and hence higher CDS spreads are expected when this volatility is higher. This variable's significance has already been tested in the literature, namely in the study of Coro et al. (2013), in which there is a positive link with CDS spreads.

To capture the volatility of the European market, the VSTOXX volatility Index has been used.

3.6 - Explanatory Variables – Other Variables

3.6.1 - Bid-Ask Spread

This variable represents a proxy for liquidity risk in the CDS market, and therefore makes sense to test its significance in the regressions. This variable should have a positive relationship with CDS spreads, as higher bid-ask spreads mean that investors demand more premium for liquidity risk, and hence higher bid-ask spreads should indicate higher CDS spreads. The motivation for using this specific proxy for liquidity risk is that, according to Fleming (2003), the bid-ask spread performs better than other proxies when measuring the liquidity in the US treasure market, and despite this study focuses on the European market exclusively, there is sufficient basis to believe that Fleming's conclusion can be applied to this case, and hence it (liq) should be a good proxy for capturing liquidity risk. This variable has been computed by taking the absolute difference between the ask and bid quotes of each CDS contract in every month.

3.6.2 - Lagged CDS spread

Finally, in order to test if past spreads influence future CDS spreads, the 1st lag of CDS spreads $(lcds)$ has been included in the regressions. According to the study of Byström (2006), the iTraxx index (index for CDS of European companies) showed strong and positive autocorrelation, which implicates a strong influence of present spreads in future ones. Given this finding, it may be valuable to analyze the impact of this variable in the prices of these financial products.

4 - Regressions

4.1 - Remarks on the data used for the regressions

Before proceeding to the regressions and analysis of the results, it is important to understand the type of data that is being used, and how it should, not only be treated but also displayed.

The data used in this paper is panel data, since it contains a time-series as well as a cross-sectional dimension[7].

To be possible to perform an accurate analysis of this data, the dependent variable (in this case the CDS prices) needs to be stationary. As such, it is necessary to perform unit root tests to the CDS data to evaluate it. As Appendix 2 shows, the CDS data in levels is not stationary – in the Fisher test we strongly reject that all panels contain unit root, but at the same time we strongly reject them to be stationary through Hadri's test – whereas the first difference of the CDS data (CDS in changes) is already stationary – in this situation, Fisher's indicates us that we should reject the null hypothesis that all panels have a unit root, and in Hadri's test we do not reject the hypothesis that all panels are stationary (see Appendix 3). In addition, these results are in concordance with the graphs for both the CDS levels and changes (see appendixes 4 and 5 respectively) – while the graph for the levels shows that the mean and variance of the data changes throughout the period, in the graph for CDS changes one can see that these parameters have the same behaviour during the whole period.

Given the previous results, the regressions will use the variables (dependent and independents) in changes, which means that the data corresponds to monthly changes instead of the actual values. This analysis is in line with the study of CGM where the first differences of the variables are also used, and it should also provide better conclusions, since analysing how CDS spreads change when other variables change constitutes a more rigorous test to the theory (Ericsson, Jacobs, & Oviedo, 2004).

4.2 - Regressions

Firstly, as well as EJO did in their study, a regression on the theoretical determinants (1) is made, followed by three individual regressions on each one of the theoretical determinants (2-

[7] More on panel data and what methodology to follow when dealing with this type of data, please refer to Baltagi (2001)

4) to examine their influence on CDS's. Then, two other regressions are made, this time to analyse the explicative power of the firm-based (5) and market-based (6) variables, respectively. Afterwards, the complete regression (7) that contains all variables is presented. There is also a multi-period analysis that refers to regression (7) evaluated over four sub-periods (pre-crisis, during crisis, during crisis extended, Eurozone crisis, after Eurozone crisis)[8]. The objective of the regressions (1-7) is to test how well these explain CDS changes, whereas the multi-period analysis seeks to investigate if all the determinants have always had the same importance for CDS changes, or if some have stopped or started to be considered after two events that have changed the world financial paradigm of this century – the 07/08 crisis, and the Eurozone crisis. In addition to the 7 main regressions, others were made to improve the analysis of the impact of certain determinants.

Regression on theoretical determinants:

$$\Delta cds_{it} = \alpha_i + \beta_1 \Delta lev_{it} + \beta_2 \Delta r_t^{10-year} + \beta_3 \Delta histvol_{it} + \varepsilon_{it} \tag{1}$$

Regression on changes in leverage:

$$\Delta cds_{it} = \alpha_i + \beta_1 \Delta lev_{it} + \varepsilon_{it} \tag{2}$$

Regression on changes in the risk-free rate:

$$\Delta cds_{it} = \alpha_i + \beta_1 \Delta r_t^{10-year} + \varepsilon_{it} \tag{3}$$

Regression on changes in historical volatility:

$$\Delta cds_{it} = \alpha_i + \beta_1 \Delta histvol_{it} + \varepsilon_{it} \tag{4}$$

Regression on firm-based variables:

$$\Delta cds_{it} = \alpha_i + \beta_1 \Delta eqret_{it} + \beta_2 \Delta impvol_{it} + \varepsilon_{it} \tag{5}$$

[8] The multi-periods sample is the following: 01/2006 to 06/2007 (pre-crisis); 07/2007 to 03/2009 (during crisis); 07/2009 to 03/2010 (during crisis extended); 04/2010 to 12/2013 (Eurozone crisis); 01/2014 to 12/2016 (after Eurozone crisis)

Regression on market-based variables:

$$\Delta cds_{it} = \alpha_i + \beta_1 \Delta slope_{it} + \beta_2 \Delta mktret_{it} + \beta_3 \Delta mktvol_{it} + \varepsilon_{it} \tag{6}$$

Regression on all variables (in changes):

$$\begin{aligned} \Delta cds_{it} = \alpha_i + \beta_1 \Delta lev_{it} + \beta_2 \Delta r_t^{2-year} + \beta_3 \Delta histvol_{it} + \beta_4 \Delta eqret_{it} + \beta_5 \Delta impvol_{it} + \beta_6 \Delta slope_{it} \\ + \beta_7 \Delta mktret_{it} + \beta_8 \Delta mktvol_{it} + \beta_9 \Delta liq_{it} + \beta_{10} \Delta lcds_{it} + \beta_{11} (\Delta r_t^{2-year})^2 + \varepsilon_{it} \end{aligned} \tag{7}$$

Since there is strong correlation between the 10-year and the 2-year yields (see Appendix 6), this paper mimics the study of EJO and therefore in equation (7), which is equivalent to the robust regression in the aforesaid study, the 10-year yield has been substituted by the 2-year German government yield. Here, the squared of the 2-year yield was also added, for reasons that have been previously explained.

Before analysing the regressions' results, it is useful to understand how these regressions work and the econometrics behind them. There are two different techniques to analyse panel data: fixed effects and random effects. According to Gujarati (2003), fixed effects models should be used when: the number of time-series data is large and the cross-sectional units are rather small; some firm-specific components that are correlated with the independent variables are omitted; the cross-sectional units are randomly drawn from a bigger sample. Indeed, according to these criteria, a fixed effects model might have seemed more appropriate for this study. Nevertheless, when performing a Hausman test on the data to decide which type of model to use, the random effects model becomes more appropriate (see Appendix 8).

After having decided the type of model that should be used, a series of tests are also required to control the data for heteroskedasticity, cross-sectional dependence of residuals, and serial correlation (see Appendix 9 for the tests and respective results), and hence ensure valid statistical inference.

After performing all the necessary tests, all the regressions were performed using Driscoll and Kraay standards errors, which allows them to be consistent with heteroskedasticity and robust to very general forms of cross-sectional and temporal dependence[9].

5 - Results

5.1 - Analysis of the Descriptive Statistics

This section will only comprise the data evaluation on changes, since this data has been proven to be stationary, contrasting with the data on levels. To get a good understanding about the evolution of all variables, descriptive statistics of not only the CDS changes but also of the changes in the explanatory variables can be found (see Appendix 7). There are also descriptive statistics that refer to different sub samples of the whole period, to allow for a more in depth analysis of the changes in the different variables (see Appendix 11)[10].

CDS spreads have increased on average 0.33 basis points during the sample period with a large standard deviation (30.83). It is interesting to see that, despite this overall increase in CDS spreads, during the period before 06/2007 CDS spreads have decreased on average 0.659 basis points, as the markets were confidents on companies' solvency and financial strength, which turn out to be a wrong assumption as we know. This situation was normalized after the crisis, as the average CDS change was of 1.121 basis points from 01/2006 and 03/2010, caused by the increase in these derivatives prices after the crisis hit the markets.

Regarding firms' leverage ratio, the average change during the whole period was of 0.023 basis points, although between 01/2006 and 03/2010, and mainly because of the 07/08 financial crisis, this value increased on average 0.148 basis points. Even more noticeable, is the fact that after 03/2010, firms on average decreased in 0.053 basis points their leverage ratios, even

[9] More information about how this method, please refer to "Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence" by Daniel Hoechle, University of Basel

[10] If, in the following analysis, the whole period is mentioned, please refer to Appendix 7, if other specific period is mentioned, please refer to Appendix 11

though this was a period characterized by low and even negative risk-free rates (10-year and 2-year rates also declined in the homologous period). This period coincided with the Eurozone crisis, in which many European firms' profits plummeted (equity returns decreased on average as well during that phase) and therefore many had to deleverage their capital structures and cut costs in order to keep their businesses going.

Throughout the sample period it it also of interest to point out the small yet positive changes in both equity and market returns, although these variables have decreased in the periods before and after the 07/08 crisis. The reasoning for the negative changes prior to the crisis can be supported by the fact that the American firms and markets were trading at all time highs before the crisis, whilst the decrease after the crisis can be explained by the Eurozone crisis. The volatility of returns and markets has also increased during the whole period, with special focus on the period that refers to the 07/08 crisis, given the deterioration of the economy, and subsequent increase of the uncertainty around future growth prospects.

Regarding the liquidity in the European CDS market, during the whole period it has increased, despite its decline before the 07/08 crisis.

5.2 - Results from Regressions

5.2.1 - Regression with Theoretical Variables (Regressions 1-4)

The results on the changes of the theoretical variables can be seen in the Appendix 12. As the results show, all three variables under this regression have found to be statistically significant when explaining the changes of CDS. Nonetheless, the explanatory power of regression 1 is rather low (14.88%) which suggests that the changes of theoretical determinants predicted by Merton's model are not sufficient when explaining changes in CDS. Regarding the signs of each of the variables' coefficients in regression 1, all three signs are in line to what the theory predicts to be the relation of each variable with CDS spreads – positive for leverage and historical volatility, and negative for the risk-free rate. Note that the risk-free rate in regressions

1 and 3 corresponds to the 10-year yield, whereas in the complete regression the yield used is the 2-year rate. This assumption was taken for the regressions to be in line with EJO's study. The regressions 2, 3 and 4, which correspond to the regressions on the individual theoretical determinants also show that each explanatory variable is statistically significant when explaining CDS changes. When analyzing each of these regressions, it is possible to see that leverage has an explanatory power of 8.64%, the risk-free rate of 4.91%, and changes in historical volatility are only able to explain only able to explain 5.86% of the changes in CDS. The results indicate that these variables explain very little of the CDS variation, and hence should be placed together with other explanatory variables. In fact, in the case of historical volatility it is possible to infer that, when compared to implied volatility (see Appendix 13), implied volatility outperforms historical, as Cao et al. (2010) conclude - higher R-squared for implied volatility (7.03%).

5.2.2 - Regression with Firm based Variables (Regression 5)

The results for this regression can be seen in Appendix 14. When regressing CDS changes on changes of the selected firm-based variables – equity returns and implied volatility – the explanatory power remains at very low levels (7.36%), which means one of two things: either the number of firm-based variables is not sufficient (which is reasonable to assume), or that it is sufficient but there are other factors that also influence CDS changes (the last part is also realistic). When looking at the coefficients of the variables, both follow the relationship predicted by the theory - equity returns negatively influence CDS and implied volatility impacts positively. Nonetheless, the most striking conclusion that can be taken from this regression is that equity returns have found to be not statistically significant for the CDS changes. This suggests that the European firms-specific returns do not affect CDS changes significantly, which can mean that other factors related to, for instance, market sentiment or economic landscape are more important. On the other hand, it is also possible there exists some multicollinearity between the two explanatory variables of regression 5, which can cause the insignificance of the equity returns.

5.2.3 - Regression with Market based Variables (Regression 6)

The results for this regression can be see in Appendix 17. When looking at the explanatory power of this regression (9.74%), one could assume that regressing CDS changes on changes in market-level variables is a better exercise than regressing on the changes of firm-level variables, even though at a still quite low degree. In fact, and given the results of regression 5, where equity returns were proved to be not significant, the previous idea might seem even more realistic. Nonetheless, from the 3 market level variables of regression 6 - slope of the yield curve, market return, and market volatility – only the last variable was found to be statistically significant, meaning that purely based on market-level variables, only the changes in the market volatility index are significant in explaining changes in CDS. Here, the same problem of multicollinearity may arise, as it is possible that the different market level variables provide redundant information. Regarding the variables' coefficients, changes on both market volatility and the slope of the yield have the same relationship with CDS changes as predicted by theory, whereas market returns have a positive coefficient, contrarily to what rationally makes sense - higher market returns should decrease CDS spreads, ceteris paribus. Nonetheless, when regressing CDS changes individually on changes in market returns (see Appendix 18), the coefficient signal is actually negative, and in line with theory.

Given the where neither equity returns nor market returns are able to explain changes in CDS, a problem arises, since it would be expected that at least one of these two variables would be significant. As such, in appendix 18, three new regressions are displayed – regression on changes in equity returns, regression on changes in market returns, and regression on both changes – with a more elucidative conclusion for the former problem. On both individual regressions, both variables are statistically significant, although equity returns are not significant at 1%, while market returns are always significant. Besides, market returns have a higher explanatory power (3.93%) than equity returns (1.98%), despite their low levels. Moreover, in the regression with both variables, only market returns were found to be statistically significant, which may indicate that in general market-level variables are indeed better determinants of CDS changes than firm-specific variables.

5.2.4 - Regression 7: Complete Regression

The results for this regression can be see in Appendix 19. Regression 7 puts all the variables identified previously, according to the literature, as possible determinants of CDS changes together. The explanatory variables of this regression are: changes in leverage ratio, changes in the risk-free rate, changes in historical volatility, changes in equity returns, changes in the slope of the yield curve, changes in market returns, changes in market volatility, changes in the bid-ask spread, changes in the lagged credit spread, and changes in the squared risk-free rate. Following the study of EJO, this regression evaluates the 2-year yield and its square instead of the 10-year rate.

The results show that, when the number of explanatory variables increase, so did the explanatory power of the regression, in this case changes in these variables are able to explain 34.33% of changes in CDS, which suggests that there are still other variables that influence CDS changes. Nonetheless, when compared with Merton's model determinants, where the R-squared was of 14.88%, this regression more than doubled its explanatory power. In addition, results show that historical volatility, equity return, market return, market volatility and the lag of CDS changes are not statistically significant, which indicates that these might not be considered for CDS changes and the pricing of these derivatives. In fact, when running a new regression without these variables, the explanatory power is almost the same (33.37%) and all the variables the regression contains are significant (see Appendix 20). This suggests that firm-specific variables such as their equity returns do not impact CDS changes significantly, and when looking at the business climate, the expectations of future interest rates (from the slope of the yield curve) are more important for CDS changes than the state of market itself, characterized by its returns.

Regarding the signs of the coefficients, only equity returns and the lagged CDS change contradict the theory, as equity returns have a positive coefficient and the lag has a negative one, contrarily to the findings of Byström study, where positive autocorrelation was found. The reason for the contrary sign of the lagged changes may be that the datasets from Byström's study was only specific to his study. Nonetheless, the fact this variable is not statistically significant suggests that CDS changes do not integrate much information about future changes.

About the changes in the bid-ask spread (the only variable that has not been discussed in the regressions so far), these have found to be statistically significant and with a positive coefficient, corroborating the positive the relationship with CDS changes according to theory.

5.2.5 - Multi-period analysis

The main purpose of this analysis is to find out if, throughout the whole sample period, some of the variables changed their significance in explaining the changes in CDS. The whole sample has been divided in 5 different sub-samples, which represent different moments during the decade under analysis: 01/2006 to 06/2007 (pre-crisis); 07/2007 to 03/2009 (during crisis); 07/2009 to 03/2010 (during crisis extended); 04/2010 to 12/2013 (Eurozone crisis); 01/2014 to 12/2016 (after Eurozone crisis). Besides the results from each sub-sample regression (see Appendix 21), there is a table that shows the significance of each variable in each of the periods (see Appendix 22).

From Appendix 22 it is possible to take some fairly interesting conclusions. From all the 11 determinants, there are 3 in which the statistical significance has changed throughout the whole period. These are the changes in leverage, the changes in equity returns, and the changes in the slope of the yield curve. Regarding the changes in leverage, that are actually statistically significant when analysing the whole sample period, in the period before the first crisis (from 01/2006 to 06/2007), these were not considered relevant when assessing the changes in CDS. The reason for this result may be that, prior to the crisis, other factors had more importance when explaining the changes in CDS, as the entities that were responsible for pricing CDS tended to overlook the degree of leverage of the underlying companies. In fact, this and other facts have led to the burst of the markets, as the prices of the securities didn't reflect the real degree of risk.

The same reasoning applies to equity returns, that prior to the same crisis were statistically significant, and after these stop being. From the point of view of an investor it makes sense that, after an event such as the 07/08 crisis, the prices of an insurance against a default of one of his investments should not be majorly supported by the returns of the underlying, as the issues of solvency and default risk are not really being considered in equity returns unless there is some public information about it, which many times there is not.

In the case of the changes in the slope of the yield, it is interesting the fact that the two periods when this variable was found to be not statistically significant coincide with the periods when the slope is less than 1%. In terms of the theoretical consequences, a low slope of the yield curve means that the expectations of the future economic conditions are not too bright, but this should not be a justification for the statistical insignificance of the variables, as poor prospects of the future economic conditions should be reflected on CDS changes and prices, that should increase. On the other hand, from an econometric point of view, the periods of non significance were periods in which the slope of the yield curve did not vary as much at stay at values really close to zero. As CDS changes continue to move, since the changes in the yield slope variable remained rather static it is possible that the effects on CDS changes were diminished to the point of not being relevant.

6 - Conclusions, limitations and final considerations

The main objective of this master thesis was to study what factors have influenced the changes in CDS spreads of European non-financial companies since 2006 until the the end of 2016. Departing from an analysis of how well the theoretical determinants derived by Merton did explain CDS variations, additional variables were subsequently considered along with a multi-period analysis of the whole sample set.

Overall, the results from the regressions are in line with the findings of the two studies that have been the main references for this thesis (EJO and CGM). Regarding the regression on the theoretical determinants, all three have found to be statistical significant when explaining the changes on CDS spreads, and all three presented the same signs as the predicted by theory. Moreover, and in line with other authors, implied volatility was found to be a better indicator for measuring firms' volatility than the historical volatility. Nevertheless, the changes on the theoretical determinants were only able to explain 14.88% of the changes in the CDS spreads during the whole period.

After regressing the CDS changes on theoretical determinants only, both firm-based and market-based variables have been added and some noticeable results have been found. First, it is important to highlight that the explanatory power of the regression with all variables was of 34.33%, more than the double of the regression on theoretical determinants. In addition, when comparing the regression of each one of the three groups of variables (theoretical, firm and market based), the results have shown that theoretical determinants have the highest explanatory power and firm-based variables the lowest. Contrarily to what was expected, though, has been the absence of statistical significance in the variables of changes in historical volatility, changes in equity return, changes in market return, changes in market volatility and the lag of CDS changes when analysing the whole sample period. In addition, both the changes in equity returns the lagged CDS changes contradict the theory predicted signs, which has also been a surprise.

Regarding the multi-period analysis, there have been three variables whose statistical significance has changed. Changes in leverage have not been statistical significance in the pre-crisis period while equity returns have only been statistical significant in the same pre-crisis period. The other variable was the changes on the slope of the yield curve, which have not been statistical significant in the pre-crisis period and in the period after the Eurozone crisis, remaining significant in the remaining periods. Another impressive result has been the explanatory power of the regression in the period after the Eurozone crisis, which was 42.98%, the highest among all regressions.

In conclusion, as theoretical determinants determinants have found to have reduced explanatory power when explaining the changes in CDS spreads, other variables variables have been considered. Nevertheless, the results obtained suggest there are still other factors which have not been considered that influence the changes in firms' CDS.

Given the nature of this project and the extent of the different sections of this thesis, I believe that the limitations encountered along the way should also be mentioned. First of all, regarding the data, as I wanted to considered only firms where all the information which did not enter in default during the period, some companies were not considered in the study, which may have impacted the results of the regressions. In addition, regarding the variables chosen, and specially regarding the firm-level variables which were only two, I believe that more should have been added, in order to try to better explain the changes in CDS spreads. As an example, the financial statement ratios used in Moody's KMV RISKCALC Model (one of the most important models used in the subject nowadays) could have been considered, since these comprise different risk factors in profitability, leverage, debt coverage, growth, liquidity activity ratios and size. In addition, variables accounting for credit ratings, likelihood of default and recovery rates could have also been considered, as these make sense to influence CDS changes. All in all, a more extensive group of variables could have been considered for the regressions, which could have resulted in higher explanatory powers. Nevertheless, this thesis has allowed me to better understand of credit default swaps work and what are the main factor that influence the changes in these derivatives prices. Regarding the first part of the thesis concerning CDS, their benefits, costs and market, it could have been interesting to include some practical cases and results from empirical studies concerning the benefits and drawbacks, as well as a section dedicated to regulation on the subject, with the objective to analyse what has been done in the world of CDS so far, and what are the prospects for the future.

All these considerations have been made according to the ultimate goal of my master thesis, which was to provide an insightful output to any person who wants to get a deep understanding about credit default swaps.

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Appendixes

Appendix 1: List of companies used in the study

Ticker	Name
AAL LN Equity	Anglo American PLC
ABE SQ Equity	Abertis Infraestructuras SA
AD NA Equity	Koninklijke Ahold Delhaize NV
AIR FP Equity	Airbus SE
AKZA NA Equity	Akzo Nobel NV
BA/ LN Equity	BAE Systems PLC
BAS GY Equity	BASF SE
BATS LN Equity	British American Tobacco PLC
BAYN GY Equity	Bayer AG
BMW GY Equity	Bayerische Motoren Werke AG
BN FP Equity	Danone SA
BP/ LN Equity	BP PLC
BT/A LN Equity	BT Group PLC
CA FP Equity	Carrefour SA
CO FP Equity	Casino Guichard Perrachon SA
CON GY Equity	Continental AG
CPG LN Equity	Compass Group PLC
DAI GY Equity	Daimler AG
DG FP Equity	Vinci SA
DGE LN Equity	Diageo PLC
DSM NA Equity	Koninklijke DSM NV
DTE GY Equity	Deutsche Telekom AG
ELE SQ Equity	Endesa SA
ELUXB SS Equity	Electrolux AB
ENEL IM Equity	Enel SpA
ENI IM Equity	Eni SpA
EOAN GY Equity	E.ON SE
ERICB SS Equity	Telefonaktiebolaget LM Ericsson
FORTUM FH Equity	Fortum OYJ
FP FP Equity	TOTAL SA
GAS SQ Equity	Gas Natural SDG SA
IBE SQ Equity	Iberdrola SA
IMB LN Equity	Imperial Brands PLC
KER FP Equity	Kering
KGF LN Equity	Kingfisher PLC
KPN NA Equity	Koninklijke KPN NV
LCL LN Equity	Ladbrokes Coral Group PLC
LHA GY Equity	Deutsche Lufthansa AG
LIN GY Equity	Linde AG
MC FP Equity	LVMH Moet Hennessy Louis Vuitton SE
ML FP Equity	Cie Generale des Etablissements Michelin

MRW LN Equity	Wm Morrison Supermarkets PLC
NESN VX Equity	Nestle SA
NG/ LN Equity	National Grid PLC
ORA FP Equity	Orange SA
PHIA NA Equity	Koninklijke Philips NV
PSON LN Equity	Pearson PLC
REL LN Equity	RELX PLC
REP SQ Equity	Repsol SA
RI FP Equity	Pernod Ricard SA
RNO FP Equity	Renault SA
RWE GY Equity	RWE AG
SAN FP Equity	Sanofi
SBRY LN Equity	J Sainsbury PLC
SGO FP Equity	Cie de Saint-Gobain
STERV FH Equity	Stora Enso OYJ
STL NO Equity	Statoil ASA
STM IM Equity	STMicroelectronics NV
TEL NO Equity	Telenor ASA
TELIA SS Equity	Telia Co AB
TIT IM Equity	Telecom Italia SpA/Milano
TKA GY Equity	thyssenkrupp AG
TSCO LN Equity	Tesco PLC
UG FP Equity	Peugeot SA
UNA NA Equity	Unilever NV
UPM FH Equity	UPM-Kymmene OYJ
VIE FP Equity	Veolia Environnement SA
VIV FP Equity	Vivendi SA
VOD LN Equity	Vodafone Group PLC
VOLVB SS Equity	Volvo AB
WKL NA Equity	Wolters Kluwer NV
WPP LN Equity	WPP PLC

Appendix 2: Unit root tests for CDS in levels

```
Fisher-type unit-root test for cds
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots          Number of panels  =     72
Ha: At least one panel is stationary       Number of periods =    132

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                 ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(144)   P      361.7565       0.0000
 Inverse normal             Z     -10.9416        0.0000
 Inverse logit t(364)       L*    -11.0097        0.0000
 Modified inv. chi-squared  Pm     12.8314        0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

```
Hadri LM test for cds
-----------------------
Ho: All panels are stationary              Number of panels  =     72
Ha: Some panels contain unit roots         Number of periods =    132

Time trend:          Not included          Asymptotics: T, N -> Infinity
Heteroskedasticity:  Not robust                              sequentially
LR variance:         (not used)
------------------------------------------------------------------------------
                     Statistic      p-value
------------------------------------------------------------------------------
 z                   136.3137        0.0000
------------------------------------------------------------------------------
```

Appendix 3: Unit root tests for CDS in changes (1st difference)

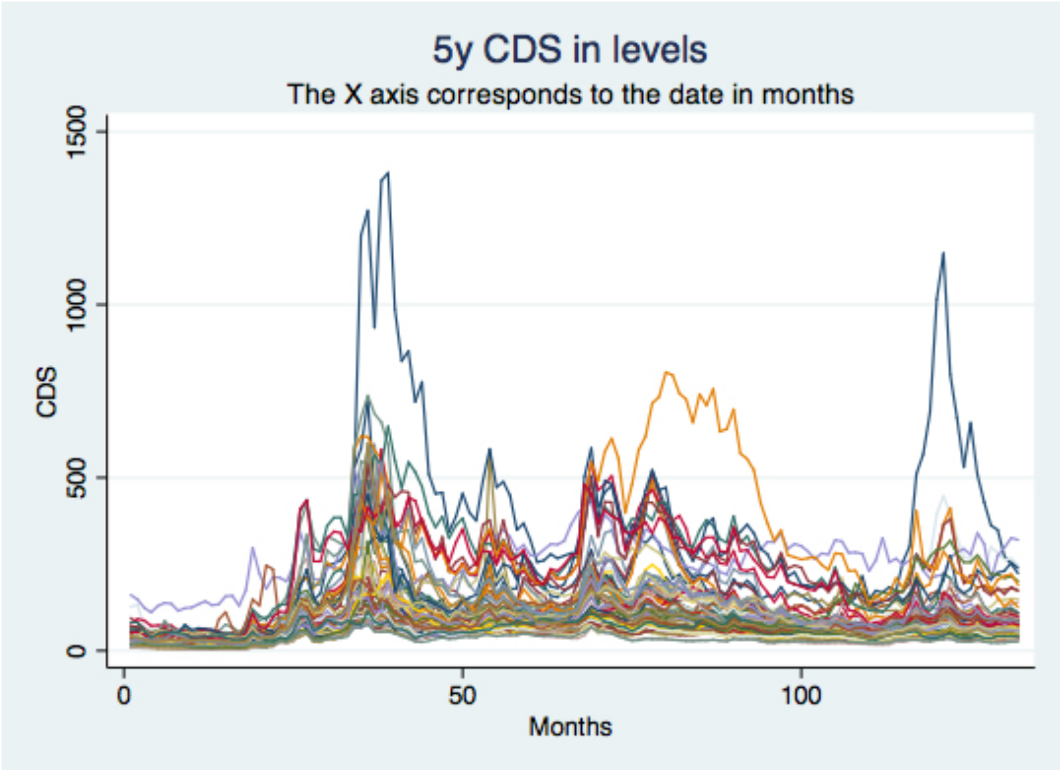
```
Fisher-type unit-root test for cds_d1
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =     72
Ha: At least one panel is stationary        Number of periods =    131

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(144)   P     5091.1859       0.0000
 Inverse normal             Z      -68.2103       0.0000
 Inverse logit t(364)       L*    -165.6275       0.0000
 Modified inv. chi-squared Pm      291.5157       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

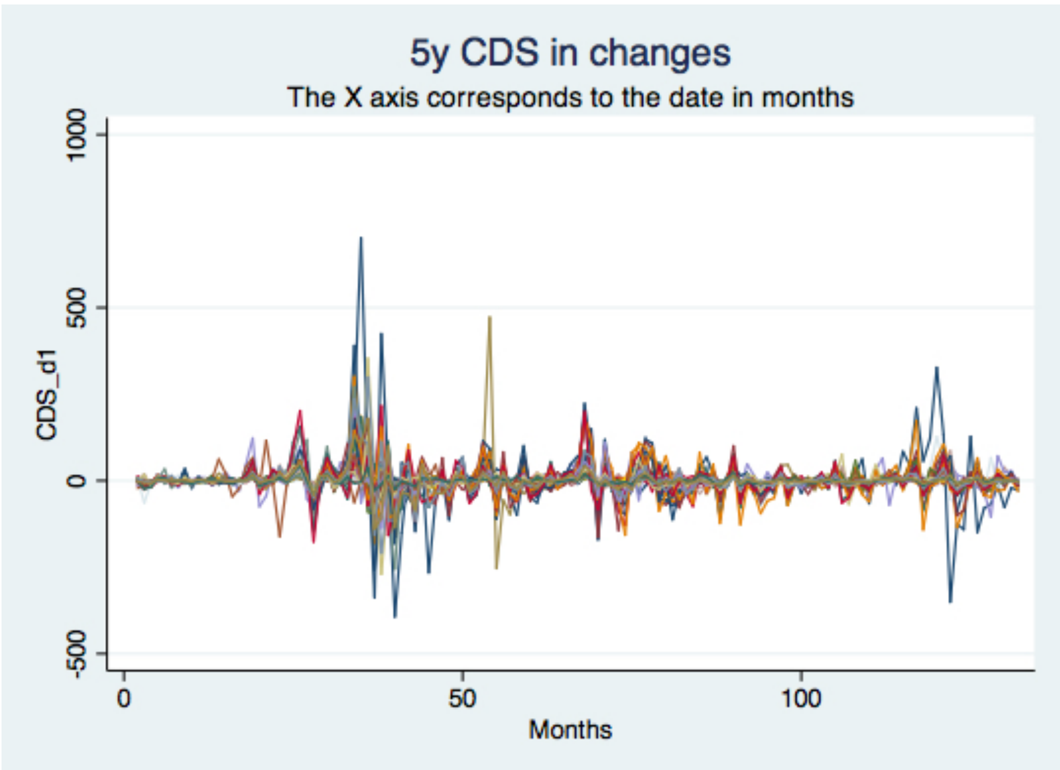
```
Hadri LM test for cds_d1
--------------------------
Ho: All panels are stationary               Number of panels  =     72
Ha: Some panels contain unit roots          Number of periods =    131

Time trend:          Not included           Asymptotics: T, N -> Infinity
Heteroskedasticity: Not robust                                sequentially
LR variance:         (not used)
------------------------------------------------------------------------------
                     Statistic      p-value
------------------------------------------------------------------------------
 z                    -5.0908        1.0000
------------------------------------------------------------------------------
```

Appendix 4: 5y CDS levels



Appendix 5: 5y CDS in changes



Appendix 6: Correlation matrix of variables (in changes)

	cds_d1	levera~1	rften_d1	rftwo_d1	sqfree~1	histvo~1	eqret_d1	impvol~1	slope_d1	mretur~1	mvol_d1
cds_d1	1.0000										
leverage_d1	0.2942	1.0000									
rften_d1	-0.2218	-0.1220	1.0000								
rftwo_d1	-0.2713	-0.1926	0.6400	1.0000							
sqfree_d1	0.2693	0.1915	-0.1249	-0.4531	1.0000						
histvol_d1	0.2423	0.1972	-0.1482	-0.3384	0.4944	1.0000					
eqret_d1	-0.1410	-0.4687	-0.0302	0.0772	-0.1029	-0.0062	1.0000				
impvol_d1	0.2656	0.2943	-0.0840	-0.2739	0.3913	0.3018	-0.3271	1.0000			
slope_d1	0.0463	0.0755	0.4641	-0.3836	0.3722	0.2120	-0.1253	0.2148	1.0000		
mreturn_d1	-0.1982	-0.2447	0.0076	0.1331	-0.1979	-0.0174	0.5158	-0.3814	-0.1444	1.0000	
mvol_d1	0.3101	0.2858	-0.2220	-0.4573	0.4335	0.2390	-0.3474	0.6124	0.2603	-0.6420	1.0000
liq_d1	0.4543	0.0844	-0.1108	-0.1412	0.1144	0.1068	0.0091	0.0464	0.0296	-0.0719	0.1038
lcds_d1	0.0605	0.0322	-0.1554	-0.1331	0.0697	0.1815	0.2559	-0.0394	-0.0333	0.2813	-0.0740

	liq_d1	lcds_d1
liq_d1	1.0000	
lcds_d1	0.1209	1.0000

Appendix 7: Descriptive statistics of variables (in changes)

Variable	Obs	Mean	Std. Dev.	Min	Max
cds_d1	9432	.3305553	30.82667	-393.495	701.738
leverage_d1	9432	.0233013	2.280468	-21.64796	34.25813
rften_d1	9432	-.0248779	.2015708	-.6420002	.411
rftwo_d1	9432	-.0284046	.1934765	-.934	.559
sqfree_d1	9432	.038236	.0980139	4.00e-06	.8723561
histvol_d1	9432	.0736939	1.827318	-14.903	19.598
eqret_d1	9432	.0303258	10.69766	-57.07751	73.05379
impvol_d1	9432	.0048436	6.085009	-55.63399	138.746
slope_d1	9432	.0035267	.1677251	-.385	.8190001
mreturn_d1	9432	.015544	5.472828	-13.3669	12.22454
mvol_d1	9432	.0173145	5.177624	-13.0193	20.2899
liq_d1	9432	.0276163	3.302356	-48.687	65.28201
lcds_d1	9360	.3705867	30.93681	-393.495	701.738

Appendix 8: Hausman test

Note: if the null hypothesis is rejected, a fixed-effects model should be used

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
 leverage_d1 |    2.327063     2.321727         .005336        .0140513
    rftwo_d1 |   -15.98713    -15.98938        .0022478        .1487202
  histvol_d1 |    1.253451     1.254975       -.0015237          .01643
    eqret_d1 |    .0410839     .0405231        .0005609        .0029011
   impvol_d1 |    .4017885     .4021019       -.0003134        .0049358
    slope_d1 |   -18.96686    -18.97073        .0038699        .1507336
  mreturn_d1 |   -.1740736    -.1741242        .0000506        .0061922
     mvol_d1 |    .5104297     .5103874        .0000423        .0074461
      liq_d1 |    3.723723     3.724075       -.0003512        .0069713
     lcds_d1 |   -.0143311    -.0142234       -.0001078        .0008054
    sqfree_d1 |   23.66956     23.66255        .0070113        .3061499
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           =        0.16
                Prob>chi2 =      1.0000
```

Appendix 9: Testing the presence of heteroskedasticity, cross-sectional dependence, and serial correlation

<< TESTING FOR CROSS-SECTIONAL DEPENDENCE (PASARAN CD TEST) >>

```
xtreg cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1
slope_d1 mreturn_d1 mvol_d1 liq_d1 lcds_d1 sqfree_d1, re
xtcsd, pesaran abs
```

Note: if we reject null, then use Driscoll and Kraay standard errors using the command xtscc

```
. xtcsd, pesaran abs


Pesaran's test of cross sectional independence =   144.903, Pr = 0.0000

Average absolute value of the off-diagonal elements =     0.267
```

<< TESTING FOR HETEROSKEDASTICITY >>

```
xtreg cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1
slope_d1 mreturn_d1 mvol_d1 liq_d1 lcds_d1 sqfree_d1, fe
xttest3
```

Note: if we reject null, then there is heteroskedasticity

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (72)  =   19665.96
Prob>chi2 =      0.0000
```

<< TESTING FOR SERIAL CORRELATION (FIRST ORDER AUTOCORRELATION) >>

```
xtserial cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1
impvol_d1 slope_d1 mreturn_d1 mvol_d1 liq_d1 lcds_d1 sqfree_d1
```

Note: if we reject null, then there is first order autocorrelation

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      71) =    149.633
           Prob > F =      0.0000
```

Appendix 11: Descriptive statistics for different periods of the sample

```
. summarize cds_d1 leverage_d1 rften_d1 rftwo_d1 sqfree_d1 histvol_d1 eqret_d1 impvol_d1 slope
> _d1 mreturn_d1 mvol_d1 liq_d1 lcds_d1 if date<19
```

Variable	Obs	Mean	Std. Dev.	Min	Max
cds_d1	1224	-.6592688	6.539268	-63.784	61.617
leverage_d1	1224	-.1815221	2.505738	-12.34709	33.23725
rften_d1	1224	.0651176	.1383796	-.161	.2819998
rftwo_d1	1224	.0886471	.1076336	-.092	.2690001
sqfree_d1	1224	.0194338	.0249398	.0001	.072361
histvol_d1	1224	.1110474	1.193219	-14.903	16.836
eqret_d1	1224	-.1295993	7.352604	-24.67998	23.88982
impvol_d1	1224	.0054355	3.233011	-22.297	16.029
slope_d1	1224	-.0235294	.074547	-.171	.091
mreturn_d1	1224	-.2503719	3.108235	-5.98678	5.941582
mvol_d1	1224	.0613941	2.771178	-4.724701	8.344
liq_d1	1224	-.0571887	.4730273	-4.281	3.043
lcds_d1	1152	-1.038141	6.28651	-63.784	61.617

```
. summarize cds_d1 leverage_d1 rften_d1 rftwo_d1 sqfree_d1 histvol_d1 eqret_d1 impvol_d1 slope_d
> 1 mreturn_d1 mvol_d1 liq_d1 lcds_d1 if date<52
```

Variable	Obs	Mean	Std. Dev.	Min	Max
cds_d1	3600	1.121155	38.57549	-393.495	701.738
leverage_d1	3600	.1476082	2.815191	-21.64796	34.25813
rften_d1	3600	-.0075	.200577	-.6420002	.411
rftwo_d1	3600	-.03994	.2582132	-.934	.559
sqfree_d1	3600	.0682507	.1438792	9.00e-06	.8723561
histvol_d1	3600	.2282578	2.450127	-14.903	19.598
eqret_d1	3600	.1064251	11.71837	-52.30019	73.05379
impvol_d1	3600	-.0123989	7.55377	-55.63399	138.746
slope_d1	3600	.03244	.1927293	-.288	.8190001
mreturn_d1	3600	.0698083	5.99599	-13.3669	12.0913
mvol_d1	3600	.09488	5.506048	-9.232998	20.2899
liq_d1	3600	.0478656	3.446595	-48.687	65.28201
lcds_d1	3528	1.37924	38.87283	-393.495	701.738

```
. summarize cds_d1 leverage_d1 rften_d1 rftwo_d1 sqfree_d1 histvol_d1 eqret_d1 impvol_d1 slope_d1 mreturn_d1
>  mvol_d1 liq_d1 lcds_d1 if date>51
```

Variable	Obs	Mean	Std. Dev.	Min	Max
cds_d1	5832	-.1574693	24.85743	-350.8701	472.219
leverage_d1	5832	-.0534313	1.871957	-19.25171	22.09163
rften_d1	5832	-.0356049	.201452	-.553	.3829999
rftwo_d1	5832	-.021284	.1387757	-.447	.508
sqfree_d1	5832	.0197084	.0431405	4.00e-06	.2580639
histvol_d1	5832	-.0217159	1.292872	-8.539	13.169
eqret_d1	5832	-.016649	10.01656	-57.07751	68.06228
impvol_d1	5832	.0154871	4.966811	-45.52	47.248
slope_d1	5832	-.014321	.1474412	-.385	.457
mreturn_d1	5832	-.0179525	5.123544	-12.72594	12.22454
mvol_d1	5832	-.0305655	4.96394	-13.0193	11.784
liq_d1	5832	.0151168	3.210324	-41.995	38.402
lcds_d1	5832	-.2395863	24.92304	-350.8701	472.219

Appendix 12: Regression on theoretical determinants

Regression 1:

```
. xtscc cds_d1 leverage_d1 rften_d1 histvol_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  3,    130)    =     20.28
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.1488
                                                 Root MSE          =   28.4454
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	3.244808	.6271052	5.17	0.000	2.004155	4.48546
rften_d1	-25.56926	8.200752	-3.12	0.002	-41.79347	-9.345056
histvol_d1	2.870519	1.321929	2.17	0.032	.2552406	5.485797
_cons	-.5927014	1.238149	-0.48	0.633	-3.042231	1.856828

Regression 2:

```
. xtscc cds_d1 leverage_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  1,    130)    =     34.02
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.0864
                                                 Root MSE          =   29.4668
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	3.972827	.6811338	5.83	0.000	2.625285	5.320369
_cons	.2379832	1.421737	0.17	0.867	-2.574753	3.050719

Regression 3:

```
. xtscc cds_d1 rften_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  1,    130)    =     11.85
maximum lag: 4                                   Prob > F          =    0.0008
                                                 R-squared         =    0.0491
                                                 Root MSE          =   30.0613
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
rften_d1	-33.90252	9.846507	-3.44	0.001	-53.38265	-14.42238
_cons	-.5128668	1.450591	-0.35	0.724	-3.382688	2.356955

Regression 4:

```
. xtscc cds_d1 histvol_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  1,    130)    =      6.93
maximum lag: 4                                   Prob > F          =    0.0095
                                                 R-squared         =    0.0586
                                                 Root MSE          =   29.9116
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
histvol_d1	4.083229	1.550687	2.63	0.009	1.015379	7.151078
_cons	.0296462	1.432171	0.02	0.984	-2.803732	2.863025

Appendix 13: Regression on implied volatility

```
. xtscc cds_d1 impvol_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  1,    130)    =     14.66
maximum lag: 4                                   Prob > F          =    0.0002
                                                 R-squared         =    0.0703
                                                 Root MSE          =   29.7250
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
impvol_d1	1.343193	.3507914	3.83	0.000	.6491942	2.037192
_cons	.3240494	1.410606	0.23	0.819	-2.466665	3.114764

Appendix 14: Regression on firm based variables (Regression 5)

```
. xtscc cds_d1 eqret_d1 impvol_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  2,    130)    =      9.67
maximum lag: 4                                   Prob > F          =    0.0001
                                                 R-squared         =    0.0736
                                                 Root MSE          =   29.6735

------------------------------------------------------------------------------
             |             Drisc/Kraay
      cds_d1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    eqret_d1 |  -.1754011   .1657594    -1.06   0.292    -.5033363    .1525341
   impvol_d1 |   1.243037   .2933178     4.24   0.000     .6627425    1.823331
       _cons |   .3298537   1.421246     0.23   0.817    -2.481911    3.141619
------------------------------------------------------------------------------
```

Appendix 17: Regression on market based variables (Regression 6)

```
. xtscc cds_d1 slope_d1 mreturn_d1 mvol_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  3,    130)    =     14.26
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.0974
                                                 Root MSE          =   29.2919

------------------------------------------------------------------------------
             |             Drisc/Kraay
      cds_d1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    slope_d1 |  -6.821804   10.40244    -0.66   0.513    -27.40179    13.75818
  mreturn_d1 |   .0146498   .3468598     0.04   0.966    -.6715709    .7008704
     mvol_d1 |   1.913223   .3236755     5.91   0.000      1.27287    2.553577
       _cons |   .3212597   1.275086     0.25   0.801    -2.201345    2.843865
------------------------------------------------------------------------------
```

Appendix 18: Regressions on equity returns and market returns

Regression on equity returns

```
. xtscc cds_d1 eqret_d1

Regression with Driscoll-Kraay standard errors   Number of obs      =      9432
Method: Pooled OLS                               Number of groups   =        72
Group variable (i): ticker                       F(  1,    130)     =      5.34
maximum lag: 4                                   Prob > F           =    0.0224
                                                 R-squared          =    0.0198
                                                 Root MSE           =   30.5222
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
eqret_d1	-.4050556	.1752099	-2.31	0.022	-.7516875	-.0584238
_cons	.342839	1.686743	0.20	0.839	-2.99418	3.679858

Regression on market returns

```
. xtscc cds_d1 mreturn_d1

Regression with Driscoll-Kraay standard errors   Number of obs      =      9432
Method: Pooled OLS                               Number of groups   =        72
Group variable (i): ticker                       F(  1,    130)     =     27.52
maximum lag: 4                                   Prob > F           =    0.0000
                                                 R-squared          =    0.0393
                                                 Root MSE           =   30.2168
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
mreturn_d1	-1.116284	.2127975	-5.25	0.000	-1.537278	-.6952895
_cons	.3479068	1.64559	0.21	0.833	-2.907697	3.60351

Regression on equity and market returns

```
. xtscc cds_d1 eqret_d1 mreturn_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  2,     130)   =     16.71
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.0413
                                                 Root MSE          =   30.1865
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
eqret_d1	-.1513237	.1707307	-0.89	0.377	-.4890939	.1864465
mreturn_d1	-.9641229	.1863066	-5.17	0.000	-1.332708	-.5955376
_cons	.3501306	1.646899	0.21	0.832	-2.908061	3.608322

Appendix 19: Regression on all variables (Regression 7)

```
. xtscc cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1 slope_d1 mreturn_d1
> mvol_d1 liq_d1 lcds_d1 sqfree_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9360
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F( 11,     129)   =     25.32
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3433
                                                 Root MSE          =   25.0884
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	2.321727	.3977159	5.84	0.000	1.534836	3.108617
rftwo_d1	-15.98938	5.59792	-2.86	0.005	-27.065	-4.913753
histvol_d1	1.254975	.6470696	1.94	0.055	-.0252681	2.535218
eqret_d1	.0405231	.1023491	0.40	0.693	-.1619772	.2430233
impvol_d1	.4021019	.1822681	2.21	0.029	.04148	.7627239
slope_d1	-18.97073	8.94574	-2.12	0.036	-36.6701	-1.271365
mreturn_d1	-.1741242	.2429431	-0.72	0.475	-.6547931	.3065447
mvol_d1	.5103874	.3345035	1.53	0.130	-.151436	1.172211
liq_d1	3.724075	.9775502	3.81	0.000	1.789968	5.658182
lcds_d1	-.0142234	.0415531	-0.34	0.733	-.0964372	.0679905
sqfree_d1	23.66255	15.16152	1.56	0.121	-6.334893	53.65999
_cons	-1.241384	.9958009	-1.25	0.215	-3.211601	.7288322

Appendix 20: Regression on significant variables

```
.
. xtscc cds_d1 leverage_d1 rftwo_d1 impvol_d1 slope_d1 liq_d1 sqfree_d1

Regression with Driscoll-Kraay standard errors   Number of obs     =      9432
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F(  6,    130)    =     48.81
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3337
                                                 Root MSE          =   25.1705
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	2.446138	.4147644	5.90	0.000	1.625576	3.2667
rftwo_d1	-20.51809	5.83174	-3.52	0.001	-32.05549	-8.980695
impvol_d1	.6835481	.2162254	3.16	0.002	.255772	1.111324
slope_d1	-18.48185	9.256681	-2.00	0.048	-36.79508	-.1686098
liq_d1	3.774972	.9682338	3.90	0.000	1.859437	5.690507
sqfree_d1	36.01446	15.04576	2.39	0.018	6.24823	65.78069
_cons	-1.728681	.9944423	-1.74	0.085	-3.696066	.2387037

Appendix 21: Regressions for the multi-period analysis

Pre crisis:

```
. xtscc cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1 slope_d1 mreturn_d1
>  mvol_d1 liq_d1 lcds_d1 sqfree_d1 if date<19

Regression with Driscoll-Kraay standard errors   Number of obs     =      1152
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F( 11,     15)    =     55.12
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.1207
                                                 Root MSE          =    6.2380
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	.1167968	.0852156	1.37	0.191	-.0648358	.2984295
rftwo_d1	13.45836	5.697514	2.36	0.032	1.314395	25.60232
histvol_d1	.1042681	.2864366	0.36	0.721	-.5062571	.7147933
eqret_d1	.0502414	.0196961	2.55	0.022	.0082602	.0922226
impvol_d1	.3371704	.0662761	5.09	0.000	.1959062	.4784347
slope_d1	-16.5434	17.51266	-0.94	0.360	-53.87075	20.78395
mreturn_d1	.1229847	.24578	0.50	0.624	-.400883	.6468524
mvol_d1	.8364018	.4303218	1.94	0.071	-.0808074	1.753611
liq_d1	2.919852	1.308218	2.23	0.041	.1314523	5.708252
lcds_d1	-.0889747	.1031089	-0.86	0.402	-.3087461	.1307967
sqfree_d1	-38.97059	30.68506	-1.27	0.223	-104.3742	26.43306
_cons	-1.531125	1.512756	-1.01	0.328	-4.755489	1.693238

During crisis:

```
. xtscc cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1 slope_d1 mreturn_d1
>  mvol_d1 liq_d1 lcds_d1 sqfree_d1 if 18<date<40
```

```
Regression with Driscoll-Kraay standard errors   Number of obs     =      9360
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F( 11,    129)    =     25.32
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3433
                                                 Root MSE          =   25.0884
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	2.321727	.3977159	5.84	0.000	1.534836	3.108617
rftwo_d1	-15.98938	5.59792	-2.86	0.005	-27.065	-4.913753
histvol_d1	1.254975	.6470696	1.94	0.055	-.0252681	2.535218
eqret_d1	.0405231	.1023491	0.40	0.693	-.1619772	.2430233
impvol_d1	.4021019	.1822681	2.21	0.029	.04148	.7627239
slope_d1	-18.97073	8.94574	-2.12	0.036	-36.6701	-1.271365
mreturn_d1	-.1741242	.2429431	-0.72	0.475	-.6547931	.3065447
mvol_d1	.5103874	.3345035	1.53	0.130	-.151436	1.172211
liq_d1	3.724075	.9775502	3.81	0.000	1.789968	5.658182
lcds_d1	-.0142234	.0415531	-0.34	0.733	-.0964372	.0679905
sqfree_d1	23.66255	15.16152	1.56	0.121	-6.334893	53.65999
_cons	-1.241384	.9958009	-1.25	0.215	-3.211601	.7288322

During crisis (extended)

```
. xtscc cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1 slope_d1 mreturn_d1
>  mvol_d1 liq_d1 lcds_d1 sqfree_d1 if 18<date<52

Regression with Driscoll-Kraay standard errors   Number of obs     =      9360
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F( 11,    129)    =     25.32
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3433
                                                 Root MSE          =   25.0884
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	2.321727	.3977159	5.84	0.000	1.534836	3.108617
rftwo_d1	-15.98938	5.59792	-2.86	0.005	-27.065	-4.913753
histvol_d1	1.254975	.6470696	1.94	0.055	-.0252681	2.535218
eqret_d1	.0405231	.1023491	0.40	0.693	-.1619772	.2430233
impvol_d1	.4021019	.1822681	2.21	0.029	.04148	.7627239
slope_d1	-18.97073	8.94574	-2.12	0.036	-36.6701	-1.271365
mreturn_d1	-.1741242	.2429431	-0.72	0.475	-.6547931	.3065447
mvol_d1	.5103874	.3345035	1.53	0.130	-.151436	1.172211
liq_d1	3.724075	.9775502	3.81	0.000	1.789968	5.658182
lcds_d1	-.0142234	.0415531	-0.34	0.733	-.0964372	.0679905
sqfree_d1	23.66255	15.16152	1.56	0.121	-6.334893	53.65999
_cons	-1.241384	.9958009	-1.25	0.215	-3.211601	.7288322

Eurozone crisis

```
. xtscc cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1 slope_d1 mreturn_d1
>  mvol_d1 liq_d1 lcds_d1 sqfree_d1 if 51<date<97

Regression with Driscoll-Kraay standard errors   Number of obs     =      9360
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F( 11,    129)    =     25.32
maximum lag: 4                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3433
                                                 Root MSE          =   25.0884
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	2.321727	.3977159	5.84	0.000	1.534836	3.108617
rftwo_d1	-15.98938	5.59792	-2.86	0.005	-27.065	-4.913753
histvol_d1	1.254975	.6470696	1.94	0.055	-.0252681	2.535218
eqret_d1	.0405231	.1023491	0.40	0.693	-.1619772	.2430233
impvol_d1	.4021019	.1822681	2.21	0.029	.04148	.7627239
slope_d1	-18.97073	8.94574	-2.12	0.036	-36.6701	-1.271365
mreturn_d1	-.1741242	.2429431	-0.72	0.475	-.6547931	.3065447
mvol_d1	.5103874	.3345035	1.53	0.130	-.151436	1.172211
liq_d1	3.724075	.9775502	3.81	0.000	1.789968	5.658182
lcds_d1	-.0142234	.0415531	-0.34	0.733	-.0964372	.0679905
sqfree_d1	23.66255	15.16152	1.56	0.121	-6.334893	53.65999
_cons	-1.241384	.9958009	-1.25	0.215	-3.211601	.7288322

After Eurozone crisis

```
. xtscc cds_d1 leverage_d1 rftwo_d1 histvol_d1 eqret_d1 impvol_d1 slope_d1 mreturn_d1
> mvol_d1 liq_d1 lcds_d1 sqfree_d1 if 96<date

Regression with Driscoll-Kraay standard errors   Number of obs     =      2592
Method: Pooled OLS                               Number of groups  =        72
Group variable (i): ticker                       F( 11,     35)    =     30.67
maximum lag: 3                                   Prob > F          =    0.0000
                                                 R-squared         =    0.4298
                                                 Root MSE          =   15.5863
```

cds_d1	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
leverage_d1	2.333571	.6201545	3.76	0.001	1.074591	3.592552
rftwo_d1	-55.39437	23.45061	-2.36	0.024	-103.0016	-7.787108
histvol_d1	.4061828	1.057229	0.38	0.703	-1.740106	2.552472
eqret_d1	-.079499	.0989829	-0.80	0.427	-.2804449	.1214469
impvol_d1	.5467776	.1776706	3.08	0.004	.1860872	.907468
slope_d1	-.160802	6.148455	-0.03	0.979	-12.64283	12.32123
mreturn_d1	-.0597508	.2206239	-0.27	0.788	-.507641	.3881395
mvol_d1	.2169582	.2677143	0.81	0.423	-.3265307	.7604471
liq_d1	4.068002	1.033446	3.94	0.000	1.969995	6.166008
lcds_d1	.0914994	.0489815	1.87	0.070	-.0079383	.1909371
sqfree_d1	-60.12832	222.1642	-0.27	0.788	-511.1456	390.8889
_cons	-1.373115	.7515832	-1.83	0.076	-2.89891	.15268

Appendix 22: Table showing the significance of variables in each sample period

Are the variables significant?	Whole period	Pre crisis	Crisis	Crisis extended	Eurozone crisis	After EUR crisis
leverage_d1	**Yes**	**No**	**Yes**	**Yes**	**Yes**	**Yes**
rftwo_d1	Yes	Yes	Yes	Yes	Yes	Yes
histvol_d1	No	No	No	No	No	No
eqret_d1	**No**	**Yes**	**No**	**No**	**No**	**No**
impvol_d1	Yes	Yes	Yes	Yes	Yes	Yes
slope_d1	**Yes**	**No**	**Yes**	**Yes**	**Yes**	**No**
mreturn_d1	No	No	No	No	No	No
mvol_d1	No	No	No	No	No	No
liq_d1	Yes	Yes	Yes	Yes	Yes	Yes
lcds_d1	No	No	No	No	No	No
sqfree_d1	No	No	No	No	No	No
R-squared	34,33%	12,07%	34,33%	34,33%	34,33%	42,98%